

Analysis of Hyperspectral Coastal Ocean Color Data

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LONG-TERM GOALS

The goal of this project is to develop spectral analysis techniques for ocean color analysis that are explicitly designed for use with hyperspectral data.

OBJECTIVES

The CoBOP program offers a rare opportunity to test any spectral analysis techniques with a wealth of remote sensing and in situ spectral data. Our objective is to develop a set of spectral analysis methods that are appropriate for remote sensing and to adapt them to remote sensing of ocean color. Our eventual objective is to expand the capability to accurately classify water types and bottom types and to extract accurate bathymetry using hyperspectral image data. The procedures will be tested and evaluated using data collected during the CoBOP field programs.

APPROACH

We have defined a three-pronged approach: 1) adapt laboratory spectroscopy techniques to remote sensing, 2) expand multispectral approaches where applicable, 3) develop novel approaches where necessary.

Our initial approach was to rely heavily on existing spectral analysis methods developed for laboratory applications. Clearly, not all methods used in spectroscopy can be directly adapted to remote sensing analysis because there are issues that are unique to remote sensing (e.g., variable illumination, atmospheric transmission, lack of reflectance standards, etc.). Nonetheless, some of the approaches should be adaptable to remote sensing.

We are also exploring ways to expand the standard multispectral approaches to spectral analysis. Their inherent limitations notwithstanding, these methods are robust and well understood. Our approach here is analogous to a change of variables or scaling to facilitate a mathematical procedure. By using derivatives or other spectral measures as the base data set, an essentially non-linear system may be rendered quasi-linear. Linear analysis tools will then be applicable.

Anticipating limits in both the previous approaches, we are also working to develop novel approaches based on radiative transfer theory. The approach is one of optimizing model prediction to match remote observations. All three approaches will rely heavily on radiative transfer modeling, although the models vary with the approach.

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WORK COMPLETED

Adapting laboratory spectroscopy methods

Three general analytical procedures have been identified as promising: 1) spectral feature extraction, 2) non-linear optimization, and 3) self-modeling. Spectral feature extraction software designed to identify spectral derivatives that are consistent for a given controlled variable, or which correlate with a known feature have been developed (Tsai and Philpot, 1998). Non-linear optimization and self-modeling procedures have also been developed. All software is in a test stage, that is, the procedures can be run by the programmers using test data sets (including real data), but have not been put in to a form easily used by other researchers. At present they have only been applied to synthetic or derived data.

Expanding multispectral approaches

The most common algorithm for estimating depth and water quality from the brightness of a remote signal relies on a simplified radiative transfer model that requires a uniform water type and bottom type. Philpot (1989) demonstrated that an equation with the same simple form, derived from a two flow model (Philpot, 1987) would lend itself to a multispectral solution which would significantly improve the accuracy of the depth estimate while simultaneously providing an estimate of the effective spectral attenuation function. The method is at least as effective and usually more effective with the increased number of spectral available in a hyperspectral system. We have generalized the solution further by replacing the original measurements with spectral derivatives and statistically optimized that solution.

Novel Approaches

The analytical spectroscopy techniques considered most appropriate for application to remote sensing all relied on a fundamental assumption of linearity in the combination of signals. For example, if two substances with different absorption coefficients are mixed together, the total absorption should be a weighted sum of the individual absorption coefficients. While this may be true in some situations for remote sensing of ocean waters, it is hard to make a very general argument, especially for coastal waters. This has led us to a pursuit of new approaches which are not so limited. The present stage of the development is radiative transfer modeling of the optical properties of the water as input to Hydrolight (Mobley, 1994). Hydrolight is being used to predict the water-leaving radiance for a wide range of water types, depths and bottom conditions. The resulting data set will be used to test inversion algorithms designed to extract information about the water type, depth and bottom type from the remote spectral data.

RESULTS

Adapting laboratory spectroscopy methods

The methods developed have been tested with synthetic data. Within the working linear assumptions they appear to be very effective. As an example, when presented with a set of mixed reflectance signals (Fig. 1a), the data are first converted into a set of absorption spectra. The self-modeling spectral decomposition algorithm will then find an optimal, minimum set of absorption spectra

that can be combined to reproduce the observed spectra. The component weights would be proportional to the concentration of the components. To the extent that the linear assumptions hold, the procedure is likely to converge on realistic base spectra.

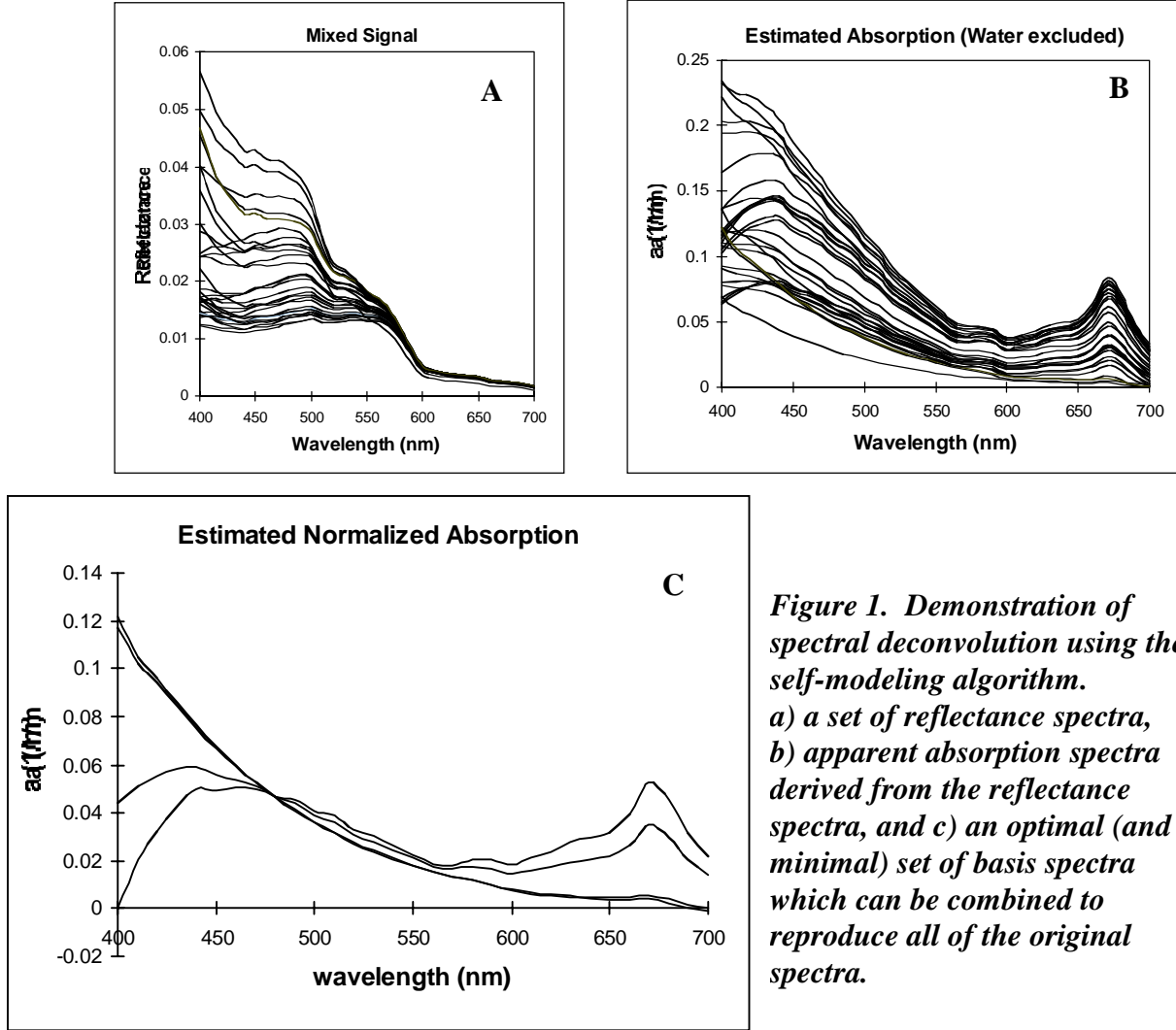


Figure 1. Demonstration of spectral deconvolution using the self-modeling algorithm. a) a set of reflectance spectra, b) apparent absorption spectra derived from the reflectance spectra, and c) an optimal (and minimal) set of basis spectra which can be combined to reproduce all of the original spectra.

Expanding multispectral approaches

The general form of the spectral solution for depth estimates is:

$$z = \frac{\frac{\partial^n}{\partial \lambda^n} (\ln(L_d - L_w) - \ln(L_b))}{\frac{\partial^n}{\partial \lambda^n} (-g)} \quad (1)$$

where L_d is the radiance at the detector, L_w is the radiance from optically deep water, L_b is a radiance term expressing the contrast between the water reflectance and the bottom reflectance, and g is an effective attenuation coefficient.

The 0th order solution ($n = 0$) corresponds to the original multispectral algorithm (Philpot, 1989). The same form of the equation is valid for any order of derivative. All solutions require that the deep water radiance (L_w) for the target water type is either known or can be estimated. A principal components (PC) analysis of the 0th order solution yields an estimate of depth as well as the effective spectral attenuation coefficient. A PC analysis of any of the derivative solutions was not as effective, largely due to the presence of outliers in the distribution of the spectral derivatives. This is illustrated in Figure 2.

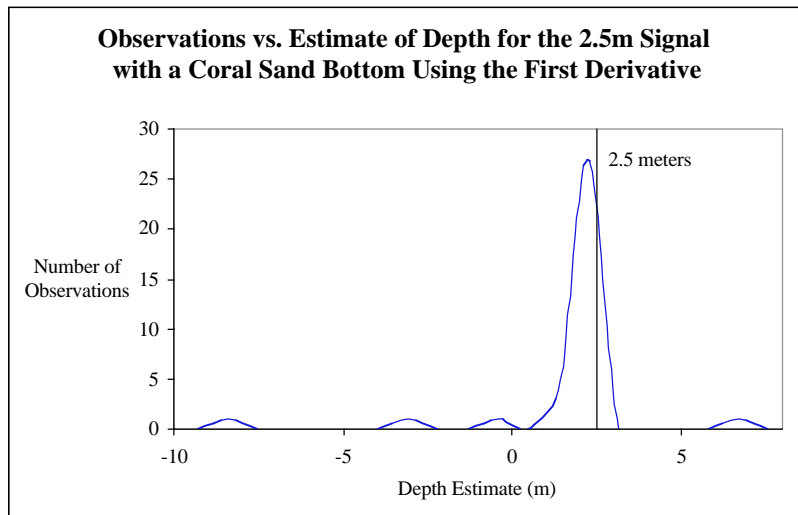


Figure 2. Quasi-normal distribution of depth estimates from the second spectral derivative. The presence of outliers in the distribution seriously degraded the depth prediction.

If the outliers are removed using a method called "outward outlier removal" which selects an optimal set of samples to produce a near normal distribution, the depth estimate is significantly improved (Kohler et al., 1998). As is shown in Figure 3, this was an improvement even over the PC analysis applied to the original radiance data.

As with the spectral decomposition method described above, the data used for this test was produced using Hydrolight. The method has yet to be tested against a real data set.

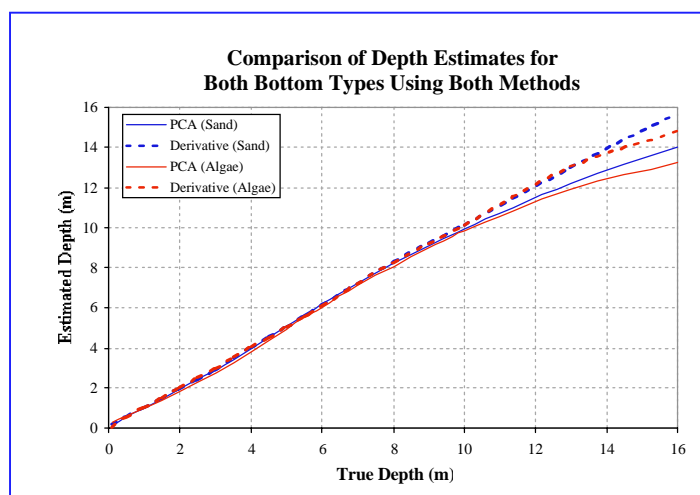


Figure 3. Comparison of depth estimates using PC analysis on amplitude data and outlier removal and with 2nd derivatives.

Novel Approaches

There are no significant results from the modeling work at this time.

IMPACT/APPLICATIONS

The tests with synthetic data indicate that there is substantial information in the hyperspectral reflectance and that it may be possible to extract at least relative spectral information about the water column, bottom type and water depth. It is not at all clear that absolute values, (e.g., absorption coefficients, absolute depths) will be accessible with remote data alone.

TRANSITIONS

The intent is to apply our techniques to data collected by other investigators in the CoBOP program and to facilitate the data analysis. Thus far we have received reflectance spectra collected by Drs. Mazel, Yentsch, Zaneveld and Zimmerman. We hope to be working with these and other data extensively in the coming year.

RELATED PROJECTS

AASERT Project, N000149710721. Results of the work performed under this funding have been incorporated into this report.

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